A Classifier for Aerial Users in 5G Networks

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***Abstract*—We propose a radio-based approach for height classification of mobile devices in cellular networks for the purpose of enabling the network infrastructure to distinguish between ground users and aerial devices like drones. The classifier is based on learning the properties of the reference signal received power (RSRP) values that each device obtains from base stations. Scenario-based simulations using the Vienna 5G System Level Simulator with adopted base station antenna patterns demonstrate the feasibility of decision tree classifiers with an average misclassification rate at about one percent with three height levels. It is shown that decision trees outperform other classification algorithms in this context.**

***Index Terms*—5G, UAV, decision trees, drones, cellular networks, system-level simulation, height classification**

I. Introduction

The integration of aerial devices like drones into terrestrial cellular networks like 5G for data transfer and command and control poses several challenges, including handovers [1] and interference [2]–[4]. To tackle these issues, it would be beneficial to have an automatic classification system that distinguishes devices as either "ground" or "aerial" [2]. Such a height classifier would enable the radio access network to decide whether to apply regular techniques (for ground devices) or aerial-specific techniques (for aerial devices) in functions like handover, resource allocation, and cell association.

This work proposes and analyzes a height classifier that operates solely on power traces in user equipment (UE) based on the reference signal received power (RSRP) from base stations (BSs). Different well-known classification algorithms are evaluated by simulation of a real-world campus scenario to choose and tune the best-performing one, namely decision trees. The entire approach does not rely on positioning systems, such as GPS or Galileo, and does not require additional hardware like pressure sensors. We have in mind flying devices like drones and air taxis at their typical flight height; however, the approach is also applicable to identify normal cell phones in high-rise buildings or airplanes during takeoff or landing.

The paper is structured as follows: Section II motivates the need to classify UEs by height and puts forward arguments for employing cellular radio signals instead of alternative technologies like sensors. Section III reviews the literature. Section IV presents the system model and simulation framework. Section V introduces the classifier. Section VI illustrates and analyzes the classifier performance. Section VII draws conclusions and proposes research directions.

II. Motivation

A. Why classify aerial users?

Today's predominant users of cellular networks are ground users — resting, walking, going in trains, or driving in vehicles. All cellular networks are optimized for these ground users. For example, the antennas of BSs are tilted downwards [5]. Due to this tilt, aerial UEs like drones primarily use the sidelobes, which entail different link properties. Another difference between ground and aerial UEs is that ground UEs hardly cause inter-cell interference (as their signal is blocked by objects like buildings). Aerial UEs have line-of-sight (LOS) links to BSs even further away, thus causing inter-cell interference [3], [4].

The first step to tackle the integration of aerial devices is that the network needs to know whether a device is a normal ground device or an aerial device. Even the most efficient algorithms will not fix any issue as long as the network does not know when to apply them. Along these lines, developing a technique that enables the radio access network to classify UEs according to their height gains substantial importance.

B. Why use cellular radio signals for classifiers?

The primary motivation behind using cellular radio-based classifiers is to avoid additional hardware like pressure sensors or ultrawideband (UWB) transceivers and give the network full control of the classification process without the need for inputs from other technologies like global navigation satellite systems (GNSS). If we rely on the UE itself to report its height provided by a different technology, the network has no means to verify this information but rather blindly trust it and use it for network resource optimization, which makes the network vulnerable to malicious usages or attacks. This could include falsely reported information, or aerial users could claim that they are ground users to potentially avoid paying higher fees for the network resources should a mobile operator decide to impose higher fees for aerial users. A network provider could also collaborate with the unmanned traffic management (UTM) competent authorities to coordinate authorized vehicles, following the recommendations by the 3GPP requirements for remote identification of the Unmanned Aerial System (UAS), summarized in 3GPP 22.125 and 23.755 [6]. These documents clearly state that "the location information from the UAV cannot be fully trusted" [7] and that "the 3GPP system shall enable a UAS to update a UTM with the live location information of a UAV and its UAV controller" [8] especially if height information is used to enforce no-fly zones or match the flight with the appropriate subscription information to the network. Moreover, our approach being solely based on basic radio hardware of the UE to perform height classification makes it feasible to be implemented on commercial off-the-shelf devices.

III. Related work

The 3GPP TS 36.331 Release 15 introduces a height-reporting parameter to allow the UE to communicate its height to the cellular network [9]. This would enable the network to first distinguish between ground UEs and aerial ones, and by consequence gives the possibility to implement novel features that consider the unique aspects and requirements of aerial UEs facilitating their integration in cellular networks. It is therefore crucial in current and future generations of mobile networks for UEs to be able to determine their height levels so that the network can differentiate aerial UEs from UEs on the ground, and serve each category or class optimally given the service requirements of each of these categories.

Location estimation in cellular networks is a well-established topic, however, the focus is typically on two-dimensional location estimation, whereas height estimation and classification has seen less interest. This includes relative positioning of the UE with respect to the BS to which it is associated [10] and multilateration techniques [11]. These techniques are beneficial for example for emergency services to localize the caller but not to classify their height. For 5G networks and beyond, current research explores the use of mm-wave and narrow beam technologies to perform accurate positioning [12]. If the accuracy in altitude is reliable enough, not only the 2D location estimation, this could be used to classify aerial UEs.

The paper [13] proposes a set of features including RSSI (Received Signal Strength Indicator), SINR (Signal-to-Interference-and-Noise Ratio), and the number of reported cells for learning-based drone detection. This is different to our approach that considers RSRP values collected by the UE from both the serving and the neighboring cells. Furthermore, we propose to classify the aerial users themselves between those flying at mid heights and others flying at high heights.

Other localization technologies offering sufficient accuracy and reliability can be used to classify whether an UE is aerial or on the ground. This includes those described in [12] or using a barometer/GPS. But this is not the aim of the paper at hand, which aims at proposing a classification approach of UEs without any external hardware or additional inputs from other sensors while keeping the computational effort reasonable.

IV. System Model and Simulator

A. Simulator

All simulations are performed using the Vienna 5G System Level Simulator, which is part of the Vienna Cellular Communications Simulators (VCCS) developed by TU Wien [14]. The tool is programmed in MATLAB in an object-oriented way and can be customized to our needs for aerial devices. The classification algorithms are run using the Statistics and Machine Learning Toolbox of MATLAB.

B. System model

The simulation was set up in a $1\,\text{km}^2$ area located around the University of Klagenfurt, Austria. Within this area, buildings are generated with random heights between 10 and 25 m on the footprints gathered with OpenStreetMap. Inside the area, 400 UEs are set per simulation. Half of these UE are ground UEs ($0-30\,\text{m}$) and half of them aerial UEs; the aerial UE are again separated half-half into low-aerial ($30-100\,\text{m}$) and high-aerial ($100-250\,\text{m}$). All users are randomly distributed inside the area, ground users were just placed outside buildings. The BS locations are taken from *Senderkataster.at* [15], which provides real-world positions. Antennas are set to a height of 30 m above ground; antennas mounted on buildings are handled in the same way as those on masts.

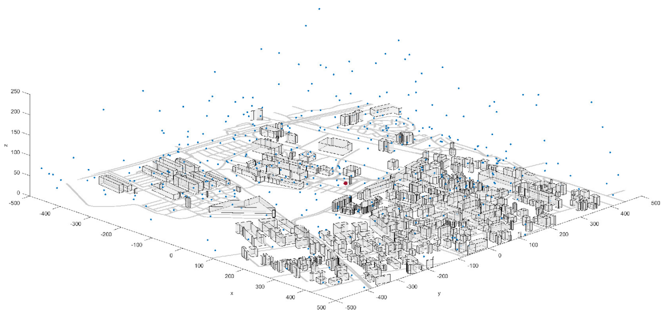


Fig. 1: Snapshot of the simulated area with buildings, base stations, ground devices, and aerial devices

C. Antennas

A three-sector antenna is used for the BSs. It is modified in a way to simulate a main lobe with two side lobes using the expressions taken from 3GPP [16] and summarized as follows:

- Vertical cut of the radiation power pattern (dB):

$$A''_{\text{dB}}(\theta'', \phi'' = 0°) = -\min\left\{12\left(\frac{\theta'' - 90°}{\theta_{3\text{dB}}}\right)^2, \text{SLA}_V\right\}$$

  with $\theta_{3\text{dB}} = 65°, \text{SLA}_V = 30\text{dB}$ and $\theta'' \in [0°, 180°]$
- Horizontal cut of the radiation power pattern (dB):

$$A''_{\text{dB}}\left(\theta = 90°'', \phi''\right) = -\min\left\{12\left(\frac{\phi''}{\phi_{3\text{dB}}}\right)^2, A_{\max}\right\}$$

  with $\phi_{3\text{dB}} = 65°, A_{\max} = 30\,\text{dB}$ and $\phi'' \in [-180°, 180°]$
- 3D radiation power pattern (dB):

$$A''_{\text{dB}}(\theta'', \phi'') = -\min\left\{-\left(A''_{\text{dB}}(\theta'', \phi'' = 0°) + A''_{\text{dB}}(\theta'' = 90°, \phi'')\right), A_{\max}\right\}$$

- Maximum directional gain of an antenna element $G_{E,\max} = 8$ dBi

The sidelobes use the same expressions with some changes:

- $\theta_{3\text{dB}}$ and $\phi_{3\text{dB}}$ are multiplied by a factor to be able to decrease the size relative to the main lobe.
- θ and ϕ are subtracted by an angle, which moves the direction of the beam relative to the main lobe.
- A''_{dB} is subtracted by a sidelobe level, which decreases the strength relative to the main lobe.

The main lobe has an elevation of 20 degrees, and $\theta_{3\text{dB}}$ and $\phi_{3\text{dB}}$ are set to 25 degrees. The maximum attenuation is set to -90 dB to accomplish a "shadow" behind the base stations. The two sidelobes are located above the main lobe with an elevation of -35 and -70 degrees relative to the main lobe. The 3 dB angles are decreased by a factor of 0.5 and 0.3 and the level is reduced by 5 and 7 dB, respectively.

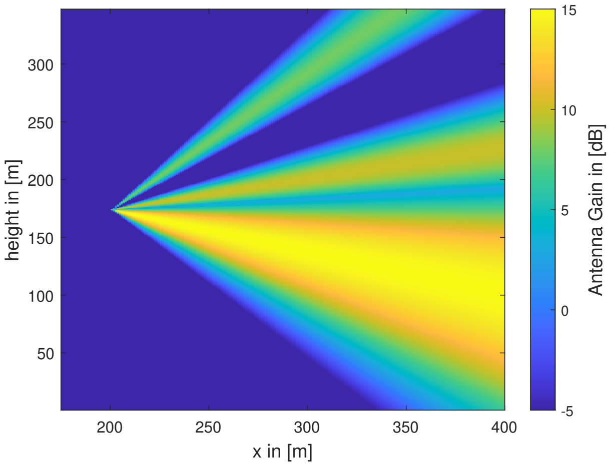


Fig. 2: Antenna pattern shown in the x/z-plane. Colors define antenna gain in decibels.

With the standard settings (maximum attenuation of 20 dB and 3 dB angle of 65 degrees), the hard drops in RSRP that occurred in real-world experiments [1] did not appear. Moreover with the maximum attenuation set to 20 dB, a UE directly behind an antenna still received a very strong signal. This was fixed by increasing it to 90 dB, which at least pushes the antennas facing away from the UE below the -120 dBm threshold. These settings are used to obtain similar RSRP values as in the real-world measurement campaign [1] carried out in the same area on our campus.

V. Classifier

A. Height groups

The UEs are classified into three groups according to their height (see Table I). The first threshold is fixed to 30 m, which is a typical height of BSs. The second threshold is set to 100 m, which is below the typical flight height of consumer drones and well below the maximum allowed flight height for drones in the category "open" defined by European Union Aviation Safety Agency (EASA) at 120 m [17].

TABLE I: Height Classification

Height	Classification
< 30 m	Ground / terrestrial
30 – 100 m	Low aerial
> 100 m	High aerial

B. Power of signals received from base stations

The classifier is based on the RSRP values that each UE obtains from its serving BS and other BSs. These values are provided by the simulator. The minimum receiver sensitivity is set to -120 dBm, a typical value for mobile devices; RSRP values below this threshold are set to -1000 dBm.

Figure 3 shows the number of antennas "visible" for each UE, where the horizonal axis sorts all UEs by their height. The red vertical lines show the classification thresholds at 30 m and 100 m; the green vertical lines show the minimum and maximum heights of building.

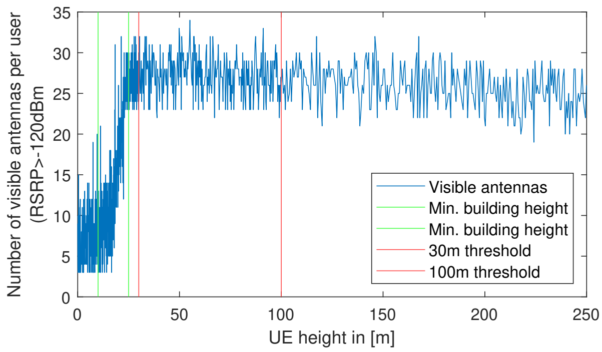


Fig. 3: Number of visible antennas per user per height

To prepare the data for the classification, the result of multiple simulations (see Section IV) was collected. The simulation data further was reduced to just contain the RSRP each user receives from each antenna (including these from cells further away), and the discretized $height\_level$ described earlier. These pairs of RSRP values and $height\_level$ are further referred to as data points. Finally, all data points which include less than three RSRP values above -120 dBm, which means less than three possible antennas, were also deleted.

C. Classification algorithms

The focus in this paper is to test the feasibility and performance of *existing, off-the-shelf algorithms* for the task of UE classification. We test four classification algorithms implemented in MATLAB on RSRP data:

- Decision trees
- K-nearest neighbors (K-NN)
- Support vector machine (SVM)
- Neural networks

VI. Results and Analysis

The classification algorithms are now tested in multiple scenarios with different movement patterns of aerial devices. Table II gives an overview of these scenarios. Before the initial test, 58,000 data points were simulated and postprocessed, accounting for 58,000 random position simulations.

TABLE II: Overview of simulations and results

Test Name	Fig.	Description
Snapshot	4	Impact of training data amount on accuracy for different classification algorithms
Vertical take-off	5a	Accuracy during takeoff and landing of a UAV
Straight flight at 40 m	5b	Accuracy during a flight on a specific height
Straight flight at 80 m	5c	Accuracy during a flight on a specific height
Impact of training data	6	More detailed look on the decision tree classifier regarding the amount of training data offered

A. *Initial tests - Snapshot*

We do initial tests to gain first insights on the influence of the training data size and the choice of algorithm on the classification accuracy. Each algorithm is tested ten times with independent training and testing data, randomly taken from the 58,000. Figure 4 shows the misclassification rates $(1 - \text{Accuracy})$ based on a training set of 1,000 data points (Figure 4a) and 50,000 points (Figure 4b). The testing set is 5,000 data points in both cases; we did not evaluate the influence of the testing set size. These tests show how accurate classifiers are at a particular point in time. The results indicate a significant advantage of decision trees and K-NN compared to SVMs and neural networks. Especially the decision tree outperforms other algorithms for both training sizes, having a misclassification rate of $4\,\%$ and $1\,\%$, respectively.

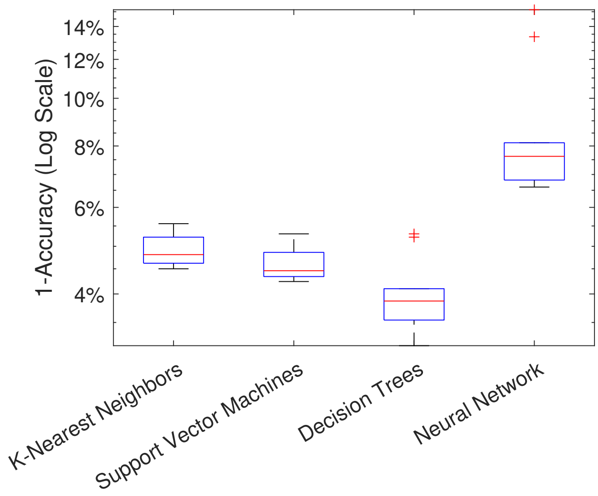
The following tests study the accuracy for moving UE. We now focus on decision trees and K-NN.

B. *Flight classification - Vertical takeoff*

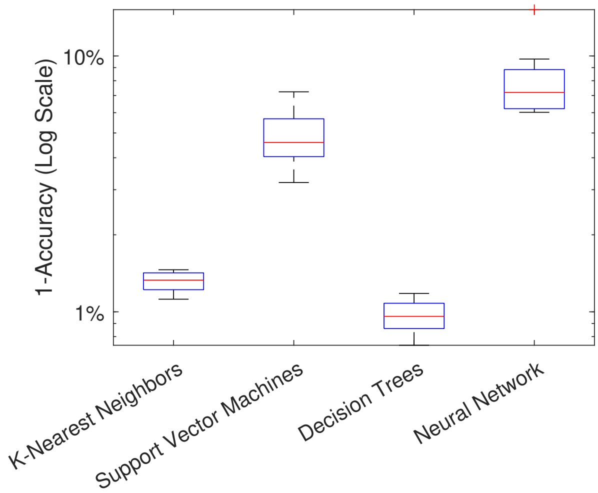
The first flight classification test is on a drone flying straight up and down, i.e., changing only its height (z-coordinate). This test should demonstrate the accuracy of height classification without any impacts due to positioning in 2D. The first plot in Figure 5 shows the classification results over time. The decision tree yields an accuracy of $97\,\%$ and the K-NN an accuracy of $89\,\%$. The results show that misclassifications occur mainly for heights close to the thresholds. A low-pass filter is a possible solution to overcome this issue.

C. *Flight classification - Straight flight*

The following tests are made with a more advanced movement pattern: a drone lifts off at position A, flies a direct path, and lands at position B. This could be a delivery drone, which starts at a store, flies straight to the customer, and lands to deliver its payload. The test should demonstrate the classification accuracy during the flight itself. Two variants are tested: (i) flights at a height of 40 m, which is above the buildings and the base stations but only 10 m above the threshold to terrestrial devices and (ii) flights at 80 m, which is already close to the threshold for high-aerial devices.



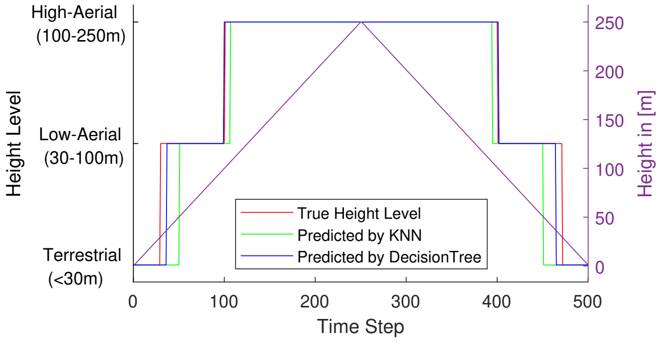
(a) Training set of 1,000 data points



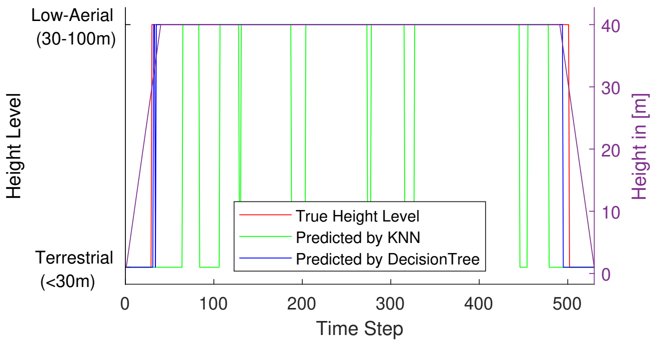
(b) Training set of 50,000 data points

Fig. 4: Accuracy of classification algorithms. Comparison of two sizes of training data.

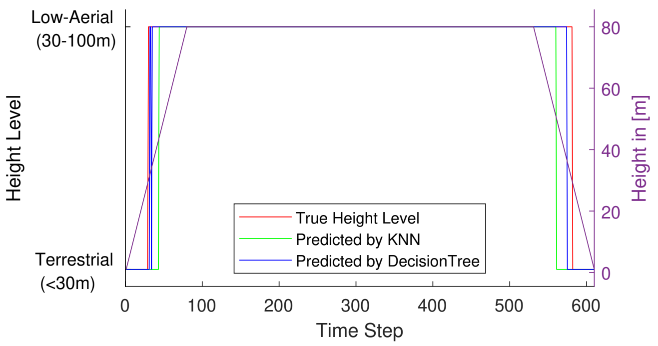
The results are given in Figure 5. The decision tree performs well with an accuracy of $98\,\%$ at both heights; the K-NN gives $77\,\%$ for 40 m and $94\,\%$ for 80 m. At 40 m, the K-NN struggles during the entire flight, whereas the decision tree classifier struggles only when crossing the thresholds. It is on top of the initial test that points out a more significant difference between the two algorithms. At 80 m, the K-NN algorithm does not struggle so much, but it still gives a worse accuracy than the tree. It was also tested at higher altitudes.



(a) Vertical Takeoff



(b) Straight flight at 40 m



(c) Straight flight at 80 m

Fig. 5: Predicted height using KNN and decision trees.

On 200 m K-NN gives 95 % and decision tree has an accuracy of 98 %.

D. *Decision tree - Impact of training data size*

The final test should show how the size of training data improves the tree classifier. For each size, 10 tests are carried out, each with a random sample of training and testing data.

Figure 6 shows the misclassification rate for six different sizes of training data from 1,000 to 50,000 data points. As expected, the accuracy improves with increasing set size. The largest training set yields a level where 99 % of all classification decisions are correct. On the lower end, even an unusually small training set of a thousand data points give

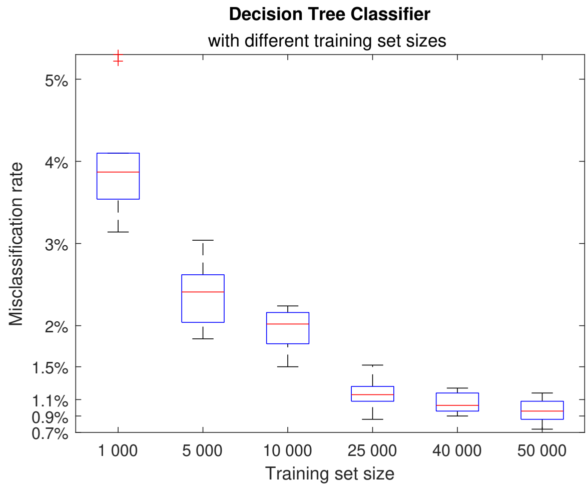


Fig. 6: Predicted Height using Decision Tree Classification

a relatively low misclassification rate of about 5 %. Clearly, the large training set requires a higher computational effort, but this is not on the side of the UE since the UE itself only uses the already fitted model and the RSRP values it stores.

VII. Conclusions and Further Work

The received signal strength can be exploited with classification algorithms to categorize cellular devices according to their height. This is useful to identify flying objects like drones in order to treat them with special network management. Simulations indicate that decision trees have a low misclassification rate for this task, in the order of one or two percent in our setup, with low computational effort in the mobile device. For comparison, GPS has an error margin of about ± 15 m with a 95 % confidence interval. The proposed approach offers standalone usability, independent of positioning systems or additional hardware. It can also be employed in conjunction with positioning systems, like to cross-validate GPS data.

We plan to test the classifier with experimental RSRP values from real-world tests. Apart from validating the simulation results, this would provide insights on the feasibility of using a model trained with simulated data in a real-world scenario. Furthermore, we will investigate to what extent the model that was learned in a certain geographical area can be transferred to another area. This would provide guidelines on whether training is required for each location or is enough to generate a model for each type of city or region of interest. Finally, we will increase the number of height levels, thus moving from height classification to height estimation.

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